International Journal of Electronics, Communication & Instrumentation Engineering Research and Development (IJECIERD)
ISSN (P): 2249-684X; ISSN (E): 2249-7951
Vol. 9, Issue 2, Dec 2019, 1-8

NEW WAVELET SHRINKAGE DE-NOISING THRESHOLDING TECHNIQUE FOR SPEECH ENHANCEMENT

DR. SHALINI SINGH

ECE Department, Graphic Era University, Dehradun, India

ABSTRACT

Wavelet shrinkage de-noising provides a new way to reduce noise present in signals. The wavelet has ability to analyze different parts of signal at different scales. The author reviews the wavelet shrinkage de-noising principal and different thresholding techniques. This paper compares the performance of different thresholding technique used in wavelet shrinkage de-noising for speech enhancement. A new thresholding technique is proposed which performs better compared to existing thresholding technique. The enhanced speech quality is measured using metric segmental- SNR.

KEYWORDS: Wavelet Shrinkage De-Noising, Speech Enhancement, Thresholding, Speech Quality & Segmental-SNR

Received: May 03, 2019; **Accepted:** May 23, 2019; **Published:** Jun 19, 2019; **Paper Id.:** IJECIERDDEC20191

Original Article

1. INTRODUCTION

Applied scientists and engineers who work with data obtained from real world know that signals do not exist without noise [2, 11]. Under the ideal conditions, the noise might decrease to such negligible levels that for all practical purposes, de-noising is not necessary. Unfortunately, we usually must remove the noise corrupting a signal to recover that signal and proceed with further data analysis.

Enthusiastic supporters have described the development of wavelet transform as revolutionizing modern signal and image processing over the past two decades [7]. Conservative observers, however describes this new field as contributing additional useful tools to growing toolbox of transform. A particular wavelet method called wavelet shrinkage de-noising has caused its zealous advocates to claim that “it offers all that we might desire of a technique [1, 6, 12], from optimality to generality”. Inquiring skeptics however might be loath to accept these claims based on asymptotic theory without persuasive evidence from real- world experiments. Fortunately a burgeoning literature is now addressing these concerns, leading to more realistic appraisal of wavelet shrinkage de-noising utility.

Wavelet shrinkage de-noising provides a new way to reduce noise in signals. Wavelet shrinkage de-noising should not be confused with smoothing (despite the use by some authors of the term smoothing as a synonym for the term de-noising) [2, 10]. Whereas smoothing removes high frequencies and retains low frequencies, de-noising attempts to remove whatever noise present and retain whatever signal is present regardless of the spectral component of noisy signal. For example, to de-noise music corrupted by noise, the high frequencies of the music should not be eliminated. Instead both the treble and bass should be preserved. Although not demonstrated here, this example of de- noising music offers an important application of wavelet shrinkage denoising for further investigation.

As developed originally by Donoho et al. [3, 4, 5], wavelet shrinkage de-noising is de-noising by shrinking coefficient wavelet transform domain. It consists of three steps

- A linear forward wavelet transform.
- A non-linear shrinkage denoising.
- A linear inverse wavelet transform.

Because of non- linear shrinking of coefficient in the transform domain, this procedure is distinct from those de-noising methods are entirely linear. Moreover, it is considered a non – parametric methods, including both linear and non-linear regression, in which parameters must be estimated for a particular model that must be assumed a priori. (For example, the most commonly used parametric method is least square regression to estimate the parameters ‘a’ and ‘b’ in model y = a*x + b).

This paper is organized as follows. Section II summarizes the wavelet shrinkage procedure. Section III provides the estimation formula for threshold value. Section IV gives segmental SNR computation formula. Section V describes the mathematical equations for different thresholding techniques. Section VI provides the experimented results. Section VII concludes the paper.

2. WAVELET SHRINKAGE DE-NOISING

Assume the observed data

X(n) = S(n) + G(n)

contains true signal S(n) with additive Gaussian noise G(n) as function in time at sample points ‘n’. Let W(.) and W-1(.) denote the forward and inverse wavelet transform operators. Let D(. , λ) denote the de-noising operator with threshold th. We intend to wavelet shrinkage de-noise X(n) in order to recover Ŝ[n] as an estimate of S[n] Then the three steps

Y = W(X)

Z = D(Y, th)

Ŝ = W-1 (Z)

summarize the wavelet shrinkage de-noising procedure [2].

The wavelet shrinkage de-noising algorithm [13] using discrete wavelet transform (DWT) is given in table 1.

Table 1: Wavelet Shrinkage De-Noising Algorithm [9]

Wavelet Shrinkage De-Noising	
1.	Select wavelet
2.	Select k ($1 \le k \le N$) decomposition level for de-noising of the coefficient Detail (Di) where i = 1, 2, …, n, when N= $\lfloor log2(L) \rfloor$, and N = length(x) that x is discrete noisy speech
3.	Compute decomposition of discrete wavelet transform (DWT) with the kth level, so the output of this step is k Detail components and kth approximate components
4.	Calculate the noise threshold for k Detail components
5.	Apply noise threshold to the k selected detail component
6.	Inverse DWT of k Detail components, and approximate components

3. THRESHOLD VALUE ESTIMATION

Donoho and Johnstone [4, 5] proposed threshold th for wavelet shrinkage de-noising.

$$\text{Threshold} \quad th = \hat{\sigma}_V \sqrt{2 \log N}$$

where $\hat{\sigma}_V{}^2$ is estimation of noise variance

N number of samples

For Gaussian White Noise

$$\hat{\sigma}_V = \frac{MAD}{0.6745} = \frac{\text{median}\left(\left|W_1^D\right|\right)}{0.6745}$$

where W_1^D is finest scale wavelet coefficients.

4. SEGMENTAL SNR COMPUTATION

The segmental SNR is computed as:

$$SNR = \frac{10}{M}\sum_{m=0}^{M-1}\log_{10}\left(\frac{\sum_{l=0}^{L-1} s^2[mL+l]}{\sum_{l=0}^{L-1}(s[mL+l]-s'[mL+l])^2}\right)$$

where s[n] is original signal

s′[n] is noisy/de - noised signal

ML is the length of signal

L is the segment length typically 10 to 20 ms

5. THRESHOLDING TECHNIQUES

5.1 Hard Threshold

Hard thresholding can be computed as

$$y = \begin{cases} x & \text{if } |x| > th \\ 0 & \text{if } |x| \le th \end{cases}$$

where

x is the original signal

y is the thresholded signal

th is the threshold value

Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. The hard thresholding creates discontinuities at x = (± th).

5.2 Soft Threshold

Soft thresholding [3] can be computed as

$$y = \begin{cases} sign(\mathrm{x})\left[|\mathrm{x}| - th\right] & if\ |\mathrm{x}| > th \\ 0 & if\ |\mathrm{x}| \le th \end{cases}$$

where

x is the original signal

y is the thresholded signal

th is the threshold value

Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the non-zero values towards zero. The Soft thresholding does not create discontinuities at x = (± th).

5.3 Super-Soft Threshold

Super-Soft thresholding is computed as

$$y = \begin{cases} \mathrm{x} - sign(\mathrm{x})\,(1-\alpha)\,th & if\ |\mathrm{x}| > th \\ \alpha\mathrm{x} & if\ |\mathrm{x}| \le th \end{cases}$$

where

x is the original signal

y is the thresholded signal

th is the threshold value

α is a weight factor ($0 < \alpha < 1$)

The Super-Soft thresholding is a modification of soft thresholding. Like the hard thresholding technique, soft thresholding also set the values to zero which are less than threshold value th, that results in voice distortion. For wavelet shrinkage speech de-noising soft thresholding technique is modified by F. Nordstrom [6]. They introduced a factor α to which gets multiplied to the values which are less than the threshold value th. If α is too low, distortion is introduced to signal and if it is too high, the noise is not reduced.

5.4 Semi-Soft Threshold

Semi-Soft thresholding is computed as

$$y = \begin{cases} \mathrm{x} & if\ |\mathrm{x}| > th1 \\ sign(\mathrm{x})\left[\dfrac{th2}{th2 - th1}\left(|\mathrm{x}| - th1\right)\right] & if\ th1 < |\mathrm{x}| < th2 \\ 0 & if\ |\mathrm{x}| \le th1 \end{cases}$$

where

x is the original signal

y is the thresholded signal

$th1$ and $th2$ are the threshold values, $th2 = \sqrt{2}\, th1$

The semi-soft thresholding is proposed by Gao and Bruce [9]. This thresholding technique avoids discontinuities of hard thresholding and magnitude reduction of soft thresholding. Here a second thresholding value introduced, namely th2 ($th2 = \sqrt{2}\, th1$). Threshold th1 is estimated from noisy signal with the usual method.

5.5 Modified Semi-Soft Threshold

We propose a new thresholding technique based on semi-soft threshold technique by introducing a factor α to which gets multiplied to the values which are less than the threshold value th1. Modified Semi-Soft Thresholding is computed as

$$y = \begin{cases} sign(x)\left[\dfrac{th2}{th2 - th1}\left(|x| - th1\right)\right] & if\ th1 < |x| < th2 \\ & if\ |x| \le th1 \end{cases}$$

where

x is the original signal

y is the threshold signal

$th1$ and $th2$ are the threshold values, $th2 = \sqrt{2}\, th1$

α is a weight factor ($0 < \alpha < 1$)

6. EXPERIMENTAL RESULTS

The performance of different thresholding techniques is compared by applying wavelet shrinkage de-noising on digital speech signals. Following procedure is adapted for a performance comparison:

- Digital samples of speech signal are taken as test signal.
- Synthetic noise added to original speech.
- Segmental SNR calculated between noisy and original speech.
- Noisy speech processed through de-nosing algorithm to get de-noised speech.
- Segmental SNR calculated between De-noised and Original Speech
- The result of one test speech signal is given in following below: Test speech signal of duration 2 seconds, sampled at 8 kHz is shown in figure 1. Test speech signal corrupted by additive white Gaussian noise. Noisy speech signal having segmental SNR of 4.2039 dB is shown in figure 2. De-noised speech using modified Semi-Soft

thresholding is shown in figure 3.

The result of one test speech signal is given in following below: Test speech signal of duration 2 seconds, sampled at 8 kHz is shown in figure 1. Test speech signal corrupted by additive white Gaussian noise. Noisy speech signal having segmental SNR of 4.2039 dB is shown in figure 2. De-noised speech using modified Semi-Soft thresholding is shown in figure 3.

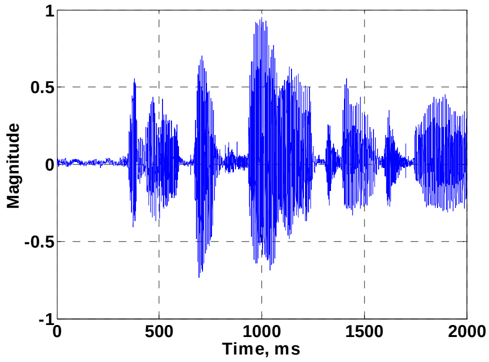

Figure 1: Original Speech Signal

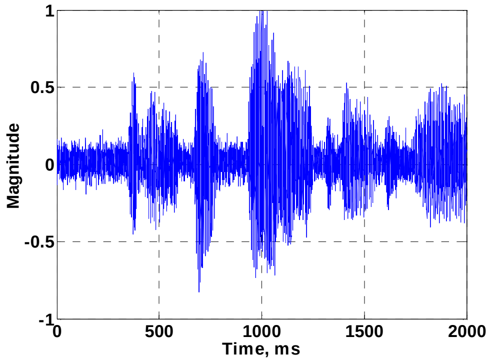

Figure 2: Noisy Speech Signal

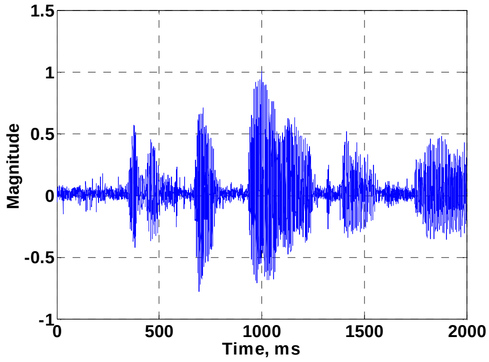

Figure 3: De-Noised Speech Signal Using Modified Semi-Soft Threshold

Segmental SNR of De-noised speech for different thresholding technique is shown in table 2.

Table 2: De-Noising Performance Comparison

S. No.	Thresholding Type	De-Noised Speech Segmental SNR in dB
1.	Hard Threshold	6.2148
2.	Soft Threshold	4.8321
3.	Super-Soft	5.182
4.	Semi-Soft Threshold	5.8963

The wavelet shrinkage de-noising using modified semi-Soft thresholding (alpha =0.3) provides 6.9186 db segmental SNR, which is maximum compared to other mentioned thresholding technique.

Table 3: Modified Semi-Soft Performance for Varying Alpha

S. No.	Alpha(α)	De-Noised Speech Segmental SNR in dB
1	0.05	6.1493
2	0.1	6.3758
3	0.2	6.7288
4	**0.3**	**6.9186**
5	0.4	6.9224
6	0.5	6.7397

The experiment was repeated on different speech signals with varying noise power. In all cases Modified Semi-Soft threshold with alpha = 0.3, provided maximum segmental SNR in de-noised speech.

7. CONCLUSIONS

- The wavelet shrinkage de-noising based on thresholding proves to be most effective procedure for speech enhancement. The experimentation on various speech signals shows that the proposed modified semi-soft thresholding performs best compared to hard, soft, semi-soft and super-soft thresholding techniques.

REFERENCES

1. *B. Vidakovic and C.B. Lozoya. (September 1998). On time-dependant wavelet de-noising, IEEE Transaction, Signal Processing, 46(9): 2549-2554*
2. *Carl Taswell. (May –June 2000). The what, how, and why of wavelet shrinkage denoising, IEEE computing in science & Engineering, 2(3):12-19*
3. *David L. Donoho. (May 1995). De-Noising by Soft Thresholding, IEEE Transaction on Information Theory, vol. 41, no. 3, pp. 613-627*
4. *D. L. Donoho and I. M. Johnston. (1994). Ideal spatial adaptation via wavelet shrinkage, Biometrika, Vol. 81, pp. 425-455*
5. *D. L. Donoho. (1993). Nonlinear Wavelet Methods for Recovery of Signals, Densities, and Spectra from Indirect and Noisy Data. http://www-stat.stanford.edu/~donoho/Reports/1993/ShortCourse.pdf*
6. *F. Nordstrom, J. Holst, and B. Lindoff. (1997). Time and frequency noise reduction in speech signals, Master's Thesis TFMS-5064, Department of Mathematics, Lund Institute of Technology, Lund, Sweden.R.*

E. Sorace, V. S. Reinhardt, and S. A. Vaughn.

7. *G. Kaiser. (1994). A Friendly Guide to Wavelets. Birkhauser.*

8. *Gopakumar, C., & Reshma, S. (2015). Wavelet Based Analysis of ECG Signal for the Detection of Myocardial Infarction Using SVM Classifier.*
9. *G. Strang and T. Naguyen. (1996). Wavelets and Filter Banks, Wellesley Cambridge Press, Boston.*
10. *H. Y. Gao and A. G. Bruce. (1995). Wave Shrink with Semisoft Shrinkage," Research Report No. 39, StatSci Division of MathSoft, Inc.*
11. *J.W. Seok and k.S. Bae. (April 1997) Speech enhancement with reduction of noise components in wavelet domain, ICASSP 1997, pages 1223-1326*
12. *S. Mallat and W. L. Hwang. (1992). Singularity Detection and Processing with Wavelets, IEEE Transaction Information Theory, 38 617-643*
13. *Y. Xu, J.B. Weaver, D.M Healy, and J. Lu. (1994). Wavelet transform domain filters: A spatially selective noise filtration technique, IEEE Transaction Image Processing, 3(6) 747-758.*
14. *Patel, A. C., & Pradhan, V. H. (2014). Wavelet galerkin scheme for nonlinear partial differential equations. Int J Res Appl Natural Soc Sci, 2(8), 69-78.*
15. *M. Srivastava, C. L. Anderson, and J. H. Freed. (2016). A new wavelet denoising method for selecting decomposition levels and noise thresholds," IEEE Access, vol. 4, pp. 3862-3877*